

STRUCTURAL STABILITY TESTS

One MAIN assumption of the classical regression is that the parameters, β , are the same for the whole sample, i.e.
for $t = 1, 2, 3, \dots, n$

$$y_t = \beta_1 + x_{t2} \beta_2 + \dots + x_{tk} \beta_k + \varepsilon_t \quad \forall t$$

$$\underset{n \times 1}{Y} = \underset{n \times k}{X} \underset{k \times 1}{\beta} + \underset{n \times 1}{\varepsilon}$$

Assume now that this is not true, i.e.

For the first n_1 observations we have

$$\textcircled{1} Y_1 = X_1 \beta^* + \varepsilon^*_{n_1}$$

$$\textcircled{2} Y_2 = X_2 \beta^{**} + \varepsilon^*_{n_2} \text{ and for the last } n_2 \text{ observations}$$

$$\text{UNDER } H_0: \beta = \beta^* = \beta^{**} \text{ we get } \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \beta + \begin{pmatrix} \varepsilon^* \\ \varepsilon^{**} \end{pmatrix} \Rightarrow$$

$$\Rightarrow \textcircled{3} Y = X\beta + \varepsilon \text{ for } n_1 + n_2 = n, \text{ NOW}$$

$$\text{Let } \hat{\varepsilon}^* = Y_1 - X_1 \hat{\beta}^* \text{ and } \hat{\varepsilon}^{**} = Y_2 - X_2 \hat{\beta}^{**}$$

$$\text{and } \hat{\varepsilon}^1 = Y - X\hat{\beta}^1. \text{ NOW}$$

$\hat{\varepsilon}^*$ and $\hat{\varepsilon}^{**}$ are the UNRESTRICTED RESIDUALS

where as $\hat{\varepsilon}^1$ are the RESTRICTED ONES

Hence

$$F = \frac{(\hat{\varepsilon}^1{}' \hat{\varepsilon}^1 - \hat{\varepsilon}^{1x}{}' \hat{\varepsilon}^1 - \hat{\varepsilon}^{1x}{}' \hat{\varepsilon}^{1x}) / k}{\frac{\hat{\varepsilon}^{1x}{}' \hat{\varepsilon}^{1x} + \hat{\varepsilon}^{1x}{}' \hat{\varepsilon}^{1x}}{n - 2k}} \stackrel{H_0}{\sim} F(k, n - 2k)$$

which is known as the Chow test.

RAMSEY RESET test

$$H_0: \varepsilon \sim N(0, \sigma^2 I_n)$$

$$H_1: \varepsilon \sim N(\mu, \sigma^2 I_n)$$

$$Y = X\beta + \varepsilon \rightarrow Y = X\beta + Z(\alpha) + \varepsilon$$

n_{β}, n_{α} n_{XV}, n_{X1}, n_{X1}

$$\hat{\beta} = (X'X)^{-1}X'Y \rightarrow \hat{Y} = X\hat{\beta}$$

$$Z = \left\{ \hat{y}_i^2, \hat{y}_i^3, \hat{y}_i^4 \right\}_{i=1, \dots, n}$$

$$H_0: \alpha = 0 \text{ v.s. } H_1: \alpha \neq 0.$$

USUAL F

$$\hat{\beta} = (X'X)^{-1}X'Y \rightarrow \hat{\varepsilon} = Y - X\hat{\beta}$$

$$\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix} = \left((X'Z)' \begin{pmatrix} Y \\ Z \end{pmatrix} \right)^{-1} (X'Y)' Y$$

$$Z = (Y_0, Y_1, Y_2)$$

$$\Rightarrow \hat{e} = Y - \begin{pmatrix} Y \\ Z \end{pmatrix}' \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix}$$

$$F = \frac{(\hat{\varepsilon}'\hat{\varepsilon} - \hat{e}'\hat{e})/3}{\hat{e}'\hat{e}/(n-k-3)} \stackrel{H_0}{\sim} F(3, n-k-3).$$

Let τ date of structural Break.
 $\tau_1 = n\alpha\%$ $\tau_2 = n(1-\alpha\%)$

F statistics show

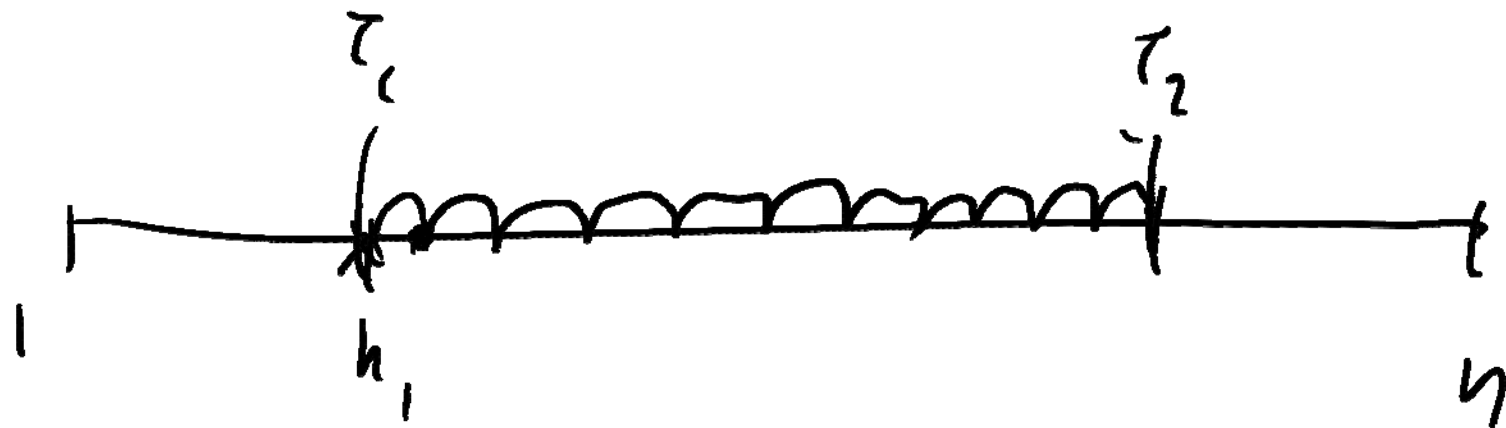
$$n_1 = \tau_1, \quad n_2 = \tau_2$$

$$\max F = \max_{\tau_1 \leq \tau \leq \tau_2} F(\tau)$$

$$\begin{aligned} \text{Exp } F &= \ln \left[\frac{1}{K} \sum_{\tau=\tau_1}^{\tau_2} \exp \left(\frac{1}{2} F(\tau) \right) \right] \\ \text{AVE } F &= \frac{1}{K} \sum_{\tau=\tau_1}^{\tau_2} F(\tau) \end{aligned}$$

NON STANDARD
CRIT. VAL.

Engle
1985
Andrews.



MAX $\rightarrow \{ F(\tau_1), F(\tau_1 + 1), F(\tau_1 + 2) \dots$

$\underbrace{F(\tau_1 + 1) \dots F(\tau_2)}_{\text{MAX}} \rightarrow \text{critical Andrew.}$

$\tau_1 + \lambda$ EXQ BREAK.

QUANT - ANDREWS

$$\underline{C}_t = \underline{\alpha} + \underline{\beta} \underline{y}_t + \varepsilon_t$$

y_t στατ. Μη στατ.

t (χρονική μετρίση)

$$\alpha^* < \alpha$$

DUMMY VARIABLE $D_t = \begin{cases} 0 & \text{χρονική στιγμή} \\ 1 & \text{χρονική στιγμή} \end{cases}$

$$C_t = \alpha + \beta \cdot D_t + \beta y_t + \varepsilon_t$$

$\beta < 0$ στατιστική διαφορά D_t
 ε χρονική στιγμή $C_t = \alpha + \beta y_t + \varepsilon_t$

ε Ποσότητα

$$C_t = \alpha + \beta + \beta y_t + \varepsilon_t$$

$$C_t = \alpha + \underbrace{\int D_t}_{\text{EIP}} + \beta y_t + \underbrace{\gamma}_{\text{EIP}} \underbrace{y_t \cdot D_t}_{\text{non.}} + \varepsilon_t$$

$$\text{EIP} \text{ non. } (D_t = 1)$$

$$C_t = \alpha + \beta + \beta y_t + \varepsilon_t$$

$$\text{EIP} \text{ non. } (D_t = 0)$$

$$C_t = \alpha + \beta y_t + \varepsilon_t$$

$$D_t = \begin{cases} 0 & \text{EIP.} \\ 1 & \text{non.} \end{cases}, \quad D_t^* = \begin{cases} 1 & \text{EIP} \\ 0 & \text{non.} \end{cases}$$

$$\alpha \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ \vdots \\ 0 \end{pmatrix}$$

$$C_t = \cancel{\alpha} + \underbrace{\int D_t}_{\text{EIP}} + \underbrace{\int^* D_t^*}_{\text{non.}} + \beta y_t + \varepsilon_t$$

$$\begin{aligned}
 \overset{\text{P.V.} \rightarrow}{r_t} &= -0.05 + 3.2 D_t + 0.82 r_{M_t} - \cancel{0.01 r_{M_t} + D_t} \\
 &\quad (0.001) \quad (0.00) \quad (0.000) \quad \cancel{(0.18)} \\
 &\quad + 1.2 S_{M_t} + 0.25 h_{M_t} - 0.24 h_{M_t} \cdot D_t \\
 &\quad (0.00) \quad (0.00) \quad (0.00)
 \end{aligned}$$

$$\begin{aligned}
 r_{M_T} &= 10\%, \quad S_{M_T} = 5\%, \quad h_{M_T} = -10\% \\
 \text{JUN.}
 \end{aligned}$$

$$\begin{aligned}
 \hat{r}_T &= -0.05 + 3.2 + 0.82 (10\%) \\
 &\quad + 1.2 (5\%) + 0.25 (-10\%) - 0.24 (-10\%) \\
 \tau \text{ NON-JUN.}
 \end{aligned}$$

$$\hat{\tilde{r}}_T = -0.05 + 0.82 (10\%) + 1.2 \cdot (5\%) + 0.25 \cdot (-10\%)$$

For our date the Andrews - Quandt
test shows a Break at January 1973

Hence we introduce a JANUARY DUMMY,
i.e.

$$JANDUM_t = \begin{cases} 1 & \text{for month} = \text{JANUARY} \\ 0 & \text{otherwise.} \end{cases}$$

MAXIMUM LIKELIHOOD method

$$Y = X\beta + \varepsilon \rightarrow \hat{\beta} = (X'X)^{-1}X'Y$$

$n \times 1$

$\hat{\beta}$ MINIMIZES $\varepsilon'\varepsilon \Rightarrow \min_{\beta} (Y - X\beta)'(Y - X\beta)$

$\hat{\beta}_{OLS}$. NOTICE THAT WE DON'T ASSUME ANY DISTRIBUTION FOR THE ERROR, ε .

ASSUME NOW THAT $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$

THEN

$$y_t = \beta_1 + \beta_2 x_{t2} + \beta_3 x_{t3} + \dots + \beta_k x_{tk} + \varepsilon_t$$

We have

$$E(y_t) = \beta_1 + \beta_2 x_{t2} + \beta_3 x_{t3} + \dots + \beta_k x_{tk}$$

and

$$V(y_t) = V(\varepsilon_t) = \sigma^2$$

Also as $\varepsilon_t \stackrel{\text{i.i.d}}{\sim} N(0) \Rightarrow y_t \sim N(\quad)$ INDEPEND.

Hence

$$y_t \sim N(\beta_1 + \beta_2 x_{t2} + \dots + \beta_k x_{tk}, \sigma^2)$$

INDEPENDENTLY.

Hence

$$f(y_t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} (y_t - b_1 - b_2 x_{t2} - \dots - b_k x_{tk})^2}$$

Now the LIKELIHOOD is given as

$$f(y_1, y_2, \dots, y_n) = \prod_{t=1}^n f(y_t)$$

and the log-LIKELIHOOD as

$$l(b_1, b_2, \dots, b_k, \sigma^2) = \sum_{t=1}^n \ln f(y_t) =$$

$$= -\frac{n}{2} \ln n - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n (y_t - b_1 - \dots - b_k x_{tk})^2$$

$$\stackrel{\sim}{=} -\frac{n}{2} \ln n - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} (Y - X\beta)' (Y - X\beta)$$

NOTICE

$$\max_{\beta} L(\beta_1, \dots, \beta_k, \sigma^2) = \max_{\beta} -\frac{1}{2\sigma^2} (Y - X\beta)' (Y - X\beta)$$

$$= \min_{\beta} \frac{1}{2\sigma^2} (Y - X\beta)' (Y - X\beta) = \min_{\beta} (Y - X\beta)' (Y - X\beta)$$

Hence $\beta_{OLS}^{\uparrow} = \beta_{OLS}^{\downarrow} = (X'X)^{-1} X'Y$

However this is not the case for σ^2

$$\frac{\partial \ell}{\partial \sigma^2} = 0 \Rightarrow -n \frac{1}{\hat{\sigma}^2} + \frac{1}{2\hat{\sigma}^4} (y - x\hat{\beta})'(y - x\hat{\beta}) = 0$$

$$\Rightarrow \hat{\sigma}_{MLE}^2 = \frac{1}{n} (y - x\hat{\beta})'(y - x\hat{\beta})$$

$$= \frac{1}{n} \hat{\varepsilon}' \hat{\varepsilon} = \frac{1}{n} \sum_{i=1}^n \hat{\varepsilon}_i^2$$

$$\hat{\sigma}_{OLS}^2 = \frac{1}{n-k} \sum_{i=1}^n \hat{\varepsilon}_i^2 \neq \hat{\sigma}_{MLE}^2$$

$$Y = X\beta + \varepsilon \quad \varepsilon \sim N(0, \sigma^2 Q)$$

Q ΘΕΤΙΚΑ ΟΡΙΣΜΕΝΗ ΣΥΜΜΕΤΡΙΚΗ
ΜΗΤΡΑ

$$V(\varepsilon_i) = \sigma^2 w_{ii}, \quad \text{cov}(\varepsilon_i, \varepsilon_j) = \sigma^2 w_{ij}$$

$$V(\underline{\varepsilon_i}) = \underline{\underline{\sigma^2}} \quad \forall i \quad \Delta \in N \quad 1 \leq i \leq n$$

$$\text{cov}(\varepsilon_i, \varepsilon_j) = 0 \quad \forall i \neq j \quad \Delta \in N \quad 1 \leq i, j \leq n$$

$$E(Y) = X\beta + E(\varepsilon) = X\beta$$

$$V(Y) = E[(Y - E(Y))(Y - E(Y))'] =$$

$$= E(\varepsilon \varepsilon') = \sigma^2 \Omega$$

$$Y \sim N(X\beta, \sigma^2 \Omega)$$

$$\ell(\beta, \sigma^2, \Omega | Y) = -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2$$

$$- \frac{1}{2} \ln |\Omega| - \frac{1}{2\sigma^2} (Y - X\beta)' \Omega^{-1} (Y - X\beta) \leftarrow$$

$$\frac{\partial \ell}{\partial \beta} = 0 \Rightarrow \frac{1}{\sigma^2} (X' \underline{Q}^{-1} Y - X' \underline{Q}^{-1} X \beta^1) = 0$$

$$\Rightarrow \beta_{MLE}^1 = (X' \underline{Q}^{-1} X)^{-1} X' \underline{Q}^{-1} Y$$

$$\frac{\partial \ell}{\partial \sigma^2} = 0 \Rightarrow \hat{\sigma}_{MLE}^2 = \frac{1}{n} (Y - X \beta^1)' (Y - X \beta^1)$$

Q ДЕТСКА ОΡΙΣΜΕΝΗ ΜΗΤΡΑ $\Rightarrow$

$$\underline{Q}^{-1} \quad \gg \quad \gg \quad \gg \quad \gg \quad \gg \quad \Rightarrow$$

$$\exists P : |P| \neq 0 : Q^{-1} = P'P$$

$$\hat{\beta}_{MLE} = (X'Q^{-1}X)^{-1}X'Q^{-1}Y =$$

$$= (X'P'PX)^{-1}X'P'PY =$$

$$= [(PX)'PX]^{-1}(PX)'PY =$$

$= \hat{\beta}_{OLS}$ THE OLS ESTIMATOR

PY ON PX

$$PY = PX\beta + P\varepsilon \quad \rightarrow \quad \hat{\beta}_{OLS} = ((PX)'PX)^{-1} (PX)'PY$$

$$Y^* = X^*\beta + \varepsilon^*$$

$$\hat{\beta}_{OLS} = (X^{*'}X^*)^{-1} X^{*'}Y^* \Rightarrow BLUE$$

if $V(\varepsilon^*) = \sigma^2 I_n$

$$\begin{aligned}
 V(\varepsilon^*) &= V(P\varepsilon) = P V(\varepsilon) P' = \\
 &= P \sigma^2 Q P' = \sigma^2 P (P'P)^{-1} P' = \\
 &= \sigma^2 \underbrace{P P'}_I \underbrace{(P'P)^{-1} P'}_I = \sigma^2 I_n.
 \end{aligned}$$

$$V(\varepsilon) = \sigma^2 Q \neq \sigma^2 I_n$$

$$\hat{\beta}_{MLE} = (X' Q^{-1} X)^{-1} X' Q^{-1} y = \hat{\beta}_{GLS}$$

GLS = GENERALISED LEAST SQUARES

$$Y = X\beta + \varepsilon$$

$n \times 1$ $n \times k$ $k \times 1$ $n \times 1$

$$\varepsilon \sim (0, \sigma^2 Q)$$

ASSUME WRONGLY $\varepsilon \sim (0, \sigma^2 I_n)$

$$\hat{\beta} = (X'X)^{-1}X'Y = \beta + (X'X)^{-1}X'\varepsilon$$

$$E(\hat{\beta}) = \beta + (X'X)^{-1}X'E(\varepsilon) = \beta$$

$$V(\hat{\beta}) = E\left[(X'X)^{-1}X'\varepsilon[(X'X)^{-1}X'\varepsilon]'\right]$$

$$= (X'X)^{-1}X'\sigma^2 Q (X'X)^{-1} \neq \sigma^2 (X'X)^{-1}$$

UNLESS $Q = I_n$

$$\begin{aligned}
V(\hat{\beta}) &= E \left[\bar{L} (\beta^1 - E(\beta)) (\beta^1 - E(\beta))' \right] \\
&= E \left[\bar{L} (\beta^1 - \beta) (\beta^1 - \beta)' \right] = \\
&= E \left[\bar{L} (X'X)^{-1} X' \varepsilon \left[(X'X)^{-1} X' \varepsilon \right]' \right] = \\
&= E \left[\bar{L} (X'X)^{-1} X' \varepsilon \varepsilon' X (X'X)^{-1} \right] = \\
&= (X'X)^{-1} X' E(\varepsilon \varepsilon') X (X'X)^{-1} = \\
&= \sigma^2 (X'X)^{-1} X' Q X (X'X)^{-1}
\end{aligned}$$

ECONOMETRIC PACKAGES EVALUATE

$$\hat{V}(\hat{\beta}) = s^2 (X'X)^{-1}$$

← NADES ⇒

$$s^2 = \frac{1}{n-k} \sum_{t=1}^n \varepsilon_t^2$$

$$V(\hat{\beta}) = \sigma^2 (X'X)^{-1} X' Q X (X'X)^{-1}$$

→ standard errors of $\hat{\beta}_i$ $i=1, 2, \dots, k$
ARE WRONG ⇒

⇒ WRONG INFERENCE,